A Turning Function Based Approach for Foot Outline Classification

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Abstract - **This study introduces a turning function based technique to classify foot outlines. Foot scans from ten males and ten females were obtained using a laser scanner. The similarities among the different foot shapes were assessed based on the Euclidean distance between turning functions. Thereafter, average linkage clustering was used to classify the differing foot outlines. Two distinct shape groups emerged for both medial and lateral sides. The presence or absence of a medial bulge results in two clusters on the medial side. Similarly, a narrow lateral side with more concavity and a wider lateral side in the midfoot region are the two clusters for the lateral side. More males (60%) showed a bulge on the medial side. The group that belongs to the narrower lateral side were predominantly females (70%). These differences in the structure of the clusters were reflected in the lack of a correlation between the medial and lateral side clusters.**

Keywords – **Foot shapes, footwear, foot outline, turning function, cluster.**

I. INTRODUCTION

Good fitting is important for footwear comfort [1]-[5]. An acceptable level of perceived fit is obtained when appropriate dimensional differences exist between a person's foot and footwear [5]. However, achieving a perfect fit is complex because fitting is primarily based on a few discrete dimensions like lengths, widths and girths [6], [7]. In addition, foot shapes differ among individuals due to differing morphological characteristics. It is well known that individual variations exist particularly at the arch and the lateral side of the foot [8], [9]. Even though foot shapes differ among individuals, research has suggested that, there are certain characteristics such as arch angle, arch height, rearfoot alignment, presence or absence of a talonavicular bulge, navicular drift and lateral concavity that help distinguish differing types of feet [10].

Thus, categorizing foot shapes into groups, based on their similarity, can be helpful for designing footwear. In order to classify foot shapes into groups, the foot shape characteristics have to be identified. Many shape recognition and matching approaches exist [11], [12], [13], [14], [15], [16]. Since the foot outline is a complex curve, the turning function approach is an appropriate and efficient method for shape matching because it can represent and match any type of curve that is complex and not closed [17] and can match both convex as well as concave polygonal shapes [11].

Thus, the primary objectives of this study was to develop a method to identify foot shape characteristics, and to classify them into groups, based on similarity, using clustering techniques.

II. METHODOLOGY

A. Participants

Twenty participants (ten males and ten females) who gave informed consent for participating in this study were recruited for the experiment. The descriptive statistics of the participants are in Table I. None of the participants had any visible foot abnormalities or foot illnesses.

B. Foot outline acquisition

The YETI^{TM} 1 laser scanner, having an accuracy of ±0.5 mm, was used to capture the 3D point cloud data of the foot surface. The captured data include the (x,y,z) coordinates of 360 points in each section. The sections are 1 mm apart and hence the total number of scanned points in any point cloud depends on foot length. The right foot of each participant was laser scanned with the body weight equally distributed on both feet.

The different types of toe shapes are quite well known. On the contrary, many researchers have been interested in characterizing and identifying the differing types of feet unique to differing populations [5], [8], [9]. Thus, our aim was to investigate the foot outline differences in the medial and lateral sides, excluding the toes. To eliminate the toe region, prior to scanning, two anatomical landmarks were placed at the side of the first (medial side) and fifth (lateral side) Metatarsal-Phalangeal joints (called M-MPJ and L-MPJ respectively) on the right foot as shown in Fig. 1.

TABLE I
DESCRIPTIVE STATISTICS OF PARTICIPANTS

	Height (cm)	Foot Length (cm)	Body Weight (kg)	Age (years)
	Mean(SD)	Mean(SD)	Mean(SD)	Mean(SD)
Females (N=10)	159.9(5.9)	23.0(1.0)	54.6(12.2)	21.3(2.4)
Males (N=10)	167.5(6.4)	24.8(0.9)	59.0(10.2)	22.0(1.8)
Total (N=20)	163.7(7.1)	23.9(1.3)	56.8(11.2)	21.7(2.1)

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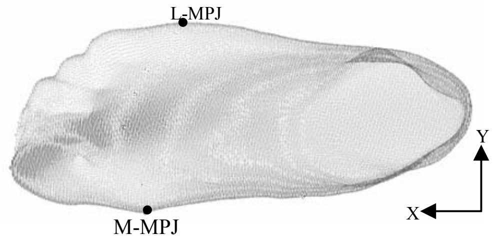

Fig. 1. 3D point cloud of foot with the two anatomical landmarks

The foot outline was generated using the following algorithm [18]:

Step 1: All scanned points no more than 40 mm above the platform were selected and projected on to the XY plane (plane of the scanner bed). This height generally represents the top view of the foot excluding the foot malleoli (ankle).

Step 2: The two points (points with minimum Y coordinate and maximum Y coordinate) on the boundary of the XY-projection were selected to represent the foot shape.

The toe region of each outline was excluded from M-MPJ to L-MPJ. A typical foot shape from M-MPJ to L-MPJ is shown in Fig. 2.

Matching foot shapes requires foot registration and the Principal Component (PC) method was used as it is a robust method when compared to other methods such as aligning along the heel-centerline [19].

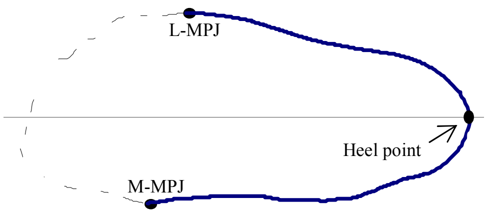

Fig. 2. Foot outline from M-MPJ to L-MPJ

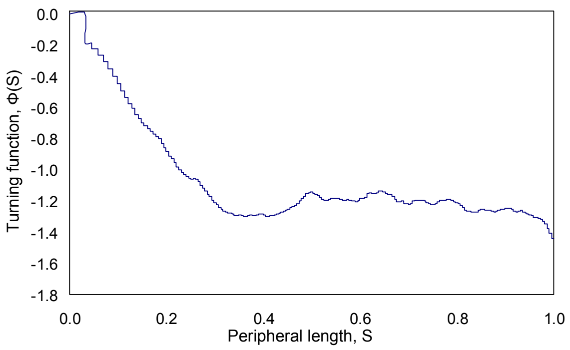

Fig. 3. Turning function, Φ(S), for the lateral side of a foot outline (peripheral length, S, as a function of the curvilinear length from heel to L-MPJ)

C. *Representation of foot shape using turning function*

The "Turning Function" measures the angle between the counter-clockwise tangent of the shape with reference to the horizontal axis (x-axis) as a function of the peripheral length (*S*), measured from a reference point on the boundary [11]. In our analysis, the initial angle was set to zero to avoid any dependency on the initial point. If the i^{th} point of the polygon has a normalized accumulated arc length L_i and a turning angle θ_i, the turning function can be represented as;

$$\Phi(S) = \sum_{i=1}^{N-1} \theta_i \chi_{[L_i, L_{i+1}]}(S) \tag{1}$$

$$\text{where} \quad \chi_{[L_i, L_{i+1}]}(S) = \begin{cases} 1 & \text{if} \quad S \in [L_i, L_{i+1}] \\ 0 & \text{otherwise} \end{cases}$$

The shape on the medial side (from M-MPJ point to most extreme point of heel in the x-axis) and the lateral side (from L-MPJ point to most extreme point of heel in the x-axis) of the foot outline were represented using separate turning functions for each subject. A typical turning function (Φ(S)) is shown in the Fig. 3.

D. *Similarity between shapes*

Similarity between shapes can be measured using the Euclidean distance between any two turning functions. This measure is called the distance function *D(. , .)* [11]. For example, the similarity between shape P and shape Q or the distance between $\theta_P(S)$ and $\theta_Q(S)$ can be represented as;

$$D(P,Q) = \left\| \theta_P(S) - \theta_Q(S) \right\|_2 = \left(\int_0^1 \left| \theta_P(S) - \theta_Q(S) \right|^2 dS \right)^{1/2} \tag{2}$$

Thus, if n number of shapes are to be compared, a n*n symmetrical matrix with zeros along the diagonal can be calculated to represent the distance function matrix. The similarity between shapes P and Q , *Sim(P , Q)* can then be calculated as;

$$Sim(P,Q) = \left(1 - \frac{D(P,Q)}{D(\max)} \right) \times 100 \tag{3}$$

Where *D*(max) = maximum value of Distance function matrix

E. *Shape Clustering*

The average linkage hierarchical clustering method was then used on the medial and lateral side turning functions. This method of clustering is known to produce a very robust nested series of partitions and it can handle very large data sets quite efficiently [20]. It is also reported that the average linkage method is superior than the single and complete linking techniques. The single linkage depends on the minimum distance and complete linkage is based on the maximum distance and it has some of the features like finding of smallest distance between centroids while minimizing variance within clusters [21].

III. ANALYSIS AND RESULTS

Fig. 4 and Fig. 5 show the dendrograms corresponding to the cluster analysis of the medial and lateral sides, respectively. The corresponding mean shapes of each cluster are shown in Fig. 6 and Fig. 7 respectively.

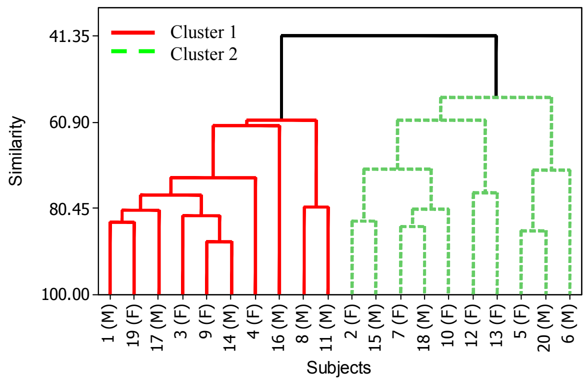

Fig. 4. Dendrogram for medial side foot outline clusters (M/F denotes Male/Female)

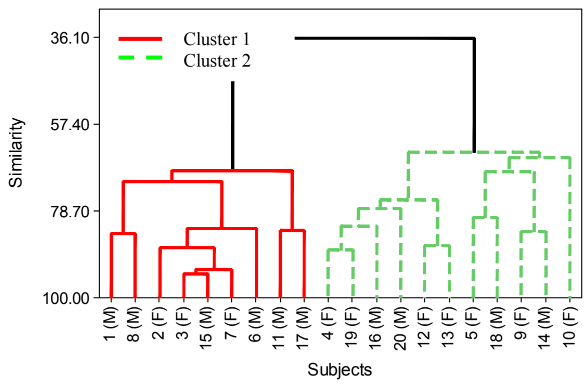

Fig. 5. Dendrogram for the lateral side foot outline clusters. (M/F denotes Male/Female)

The subject composition in the two clusters is shown in Table II. The medial side cluster 1 appears to compose of more males and, in contrast, 60% female subjects belong to cluster 2. Fig. 6 shows that cluster 1 has a significant medial bulge compared to cluster 2.

Cluster 2 in the lateral side has more females than cluster 1 (Table II). As shown in Fig. 7, cluster 2 has a narrower midfoot than cluster 1.

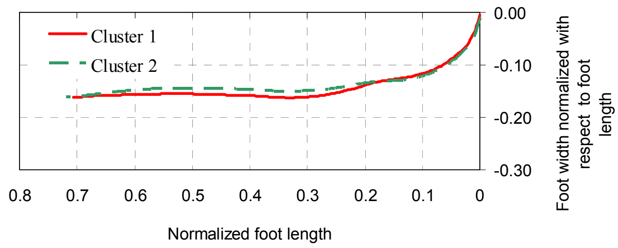

Fig. 6. Mean outline shapes of the medial side clusters

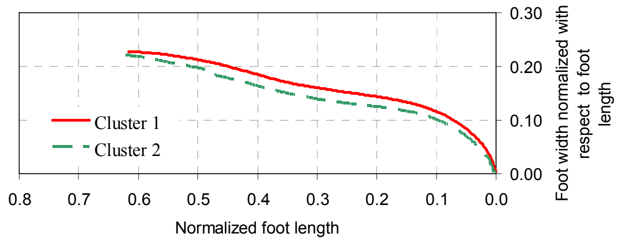

Fig. 7. Mean outline shapes of the lateral side clusters

TABLE II
SUBJECT COMPOSITION IN FOOT OUTLINE CLUSTERS

	Medial Side		Lateral Side	
	Male	Female	Male	Female
Cluster 1	6	4	6	3
Cluster 2	4	6	4	7

The correlations between the medial and lateral side clusters were not significant (Pearson correlation coefficient = 0.101, p = 0.673).

IV. DISCUSSION

In this study, we have introduced a method to classify foot shapes using digital data. The average linkage clustering technique was used to determine the group compositions of similar shapes.

Analyses showed that the cluster with more female subjects exhibits a narrower lateral side with more concavity in the midfoot region while the other cluster has a wider lateral side. The splitting of the two sides of the foot allowed us to determine this difference. Previous researchers [8], [9] have alluded to the fact that males are more prone to have broader feet than females and that there are dimensional differences between the two genders. Our result validates that the female foot shape is not simply a scale down version of male foot shape.

Fig. 6 shows that the shape differences on the medial side are due to the presence or absence of a medial bulge in the midfoot region, primarily due to the overhang of the navicular bone [22]. More males (60%) seem to have this medial bulge when compared to females (40%).

No significant correlation exist between the feet that have a medial bulge and a lateral concavity (coefficient = 0.101, p= 0.673), which is consistent with the findings of

Kouchi [22]. The lack of any significant correlation can be due to the differential loading on the two sides of the foot resulting in a medial bulge or an increased level of lateral concavity. The analyses show significant differences in the shapes in the two sides of any foot. Most shoes have no room to accommodate a medial bulge or an increased lateral concavity [22] and when a shoe is worn, it is possible that these foot characteristics impact the fit between foot and shoe [5]. Understanding the foot shape differences will allow footwear designers to develop footwear with a higher level of perceived fit.

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